## AMENDMENTS TO THE CLAIMS

This listing of claims will replace all prior versions, and listings, of claims in the application:

### Listing of Claims

Original claims 1-22 and amended claims 1-21 are cancelled.

Claim 23 (new): A method for the automatic online detection and classification of anomalous objects in a data stream, comprising the steps of:

a) detecting at least one incoming data stream containing normal and anomalous objects,

b) constructing a geometric representation of normality of the incoming objects of the data stream at a time ($t_1$) subject to at least one predefined optimality conditions,

c) geometrically representing an optimal normality,

d) adapting the geometric representation of normality in respect to at least one received object at a time ($t_2$), which is greater than $t_1$, wherein the adaptation is subject to at least one predefined optimality condition,

e) determining a normality/anomality classification for received objects at $t_2$ in respect to the geometric representation of normality,

f) classifying normal objects and anomalous objects based on the generated normality classification and generating a data set describing the anomalous data for further processing.

Claim 24 (new): The method according to claim 23, wherein the geometric representation of normality is a parametric boundary hypersurface using the enclosure of the minimal volume or the minimal volume estimate among all possible surfaces as an optimality condition.

Claim 25 (new): The method according to claim 24, wherein the hypersurface is constructed in the space of original measurements of least one incoming data stream or in a space obtained by a nonlinear transformation thereof.

Claim 26 (new): The method according to claim 23, wherein the optimality condition, used to construct the parametric boundary hypersurface, is a predefined condition.

Claim 27 (new): The method according to claim 23, wherein the anomalous objects are determined as the ones lying outside of the geometrical representation of normality.

Claim 28 (new): The method according to claim 23, wherein the adaptation of the geometric representation of normality comprises an automatic adjustment of parameters $x_i$ of the geometric representation of normality to incorporate at least one new object while maintaining the optimality of the geometric representation of normality.

Claim 29 (new): The method according to claim 23, wherein the adaptation of the geometric representation of normality comprises an automatic adjustment of parameters $x_i$ of the geometric representation of normality to remove the least-relevant object, while maintaining the optimality of the geometric representation of normality.

Claim 30 (new): The method according to claim 23, wherein the geometric representation of normality is generated with a Support Vector Machine method, generating a parametric vector x to describe the representation.

Claim 31 (new): The method according to claim 23, wherein a temporal change of the geometrical representation of normality is stored for the evaluation of temporal trend in the data stream.

Claim 32 (new): The method according to claim 23, wherein the geometric representation of normality is a sphere or any part thereof.

Claim 33 (new): The method according to claim 23, wherein the incoming data stream comprises data packets in communication networks or representations thereof.

Claim 34 (new): The method according to claim 23, wherein the data objects comprise entries originating from the logging in process in at least one computer or representations thereof.

Claim 35 (new): The method according to claim 33, wherein the determination of normality of the received data packets distinguishes normal incoming data stream from anomalous data, whereby a means for determining the normal and anomalous data generates a warning message.

Claim 36 (new): The method according to claim 23, wherein the construction and update of the geometric representation of normality in which the coordinate system in which the representation is constructed is fixed to some point in the data space or in the feature space.

Claim 37 (new): The method according to claim 36, wherein the center of the coordinate system coincides with the center of mass of the data space in the original or in the feature space.

Claim 38 (new): The method according to claim 36, wherein the decision on normality or anomality of an object is decided upon its norm in a data-centered coordinate system, a feature-space-centered coordinate system, or by the radius of the hypershere centered at the center of the origin in the coordinate system and encompassing the given objects.

Claim 39 (new): The method according to claim 36, wherein the update of the representation includes the update of the coordinate system.

Claim 40 (new): The method according to claim 36, wherein the update of coordinate system includes the update of a center of coordinates.

Claim 41 (new): The method according to claim 36, wherein importation of a new object is included as a part of the update of the norms of all objects in the working set so as to bring them in the new coordinate system corresponding to an expanded working set.

Claim 42 (new): The method according to claim 37, wherein removal of the object is included as a part of the update of the norms of all objects in the working set so as to bring them in the new coordinate system corresponding to a contracted working set.

Claim 43 (new): A system for the automatic online detection and classification of anomalous objects in a data system, comprising:

a) a detecting means for detecting at least one incoming data stream containing normal and anomalous objects,

b) an automatic online anomaly detection engine, comprising:

an automatic construction means for constructing a geometric representation of normality for the incoming objects of the data stream at a time ($t_1$) subject to at least one predefined optimality condition, with an automatic online adaptation means for adapting the geometric representation of normality in respect to received at least one received object at a time ($t_2$), which is greater than $t_1$, the adaptation being subject to at least one predefined optimality condition,

a means for geometrically representing an optimal normality, and

an automatic online determination means for determining a normality classification for received objects at $t_2$ in respect to the geometric representation of normality, and

c) an automatic classification means for classifying normal objects and anomalous objects based on the generated normality classification and generating a data set describing the anomalous data for further processing.